Artificial intelligence or human: when and why consumers prefer AI recommendations

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Abstract

Purpose – Artificial intelligence (AI) is revolutionizing product recommendations, but little is known about consumer acceptance of AI recommendations. This study examines how to improve consumers' acceptance of AI recommendations from the perspective of product type (material vs experiential).

Design/methodology/approach – Four studies, including a field experiment and three online experiments, tested how consumers' preference for AI-based (vs human) recommendations differs between material and experiential product purchases.

Findings – Results show that people perceive AI recommendations as more competent than human recommendations for material products, whereas they believe human recommendations are more competent than AI recommendations for experiential products. Therefore, people are more (less) likely to choose AI recommendations when buying material (vs experiential) products. However, this effect is eliminated when is used as an assistant to rather than a replacement for a human recommendation.

Originality/value – This study is the first to focus on how products' material and experiential attributes influence people's attitudes toward AI recommendations. The authors also identify under what circumstances resistance to algorithmic advice is attenuated. These findings contribute to the research on the psychology of artificial intelligence and on human–technology interaction by investigating how experiential and material attributes influence preference for or resistance to AI recommenders.

Keywords AI recommendations, Product type, Competence perception, AI assistant

Paper type Research paper

1. Introduction

The proliferation of artificial intelligence (AI) technologies has led to a substantial increase in the use of AI recommendations. In the domain of e-commerce (e.g. Amazon), personalized recommendations are generated for users based on their past search and browsing histories. Similarly, in the domain of search engines (e.g. Google), recommendation systems assist users in locating relevant information and predicting their interests with high accuracy. In service industries, tourism websites such as TripAdvisor can recommend tourist routes and automatically plan itineraries for consumers. Despite the extensive usage of AI recommendations, consumers exhibit skepticism towards such recommendation, which brings unfavorable impacts for enterprises that aim to promote AI technologies (Yeomans *et al.*, 2019; Bonaccio and Dalal, 2006; Yaniv and Kleinberger, 2000; Yaniv, 2004).

Previous research has investigated people's acceptance of AI recommendations in various domains, including medical, financial, outcome forecasting (Castelo *et al.*, 2019; Dietvorst

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et al., 2015; Leung *et al.*, 2018; Huang and Rust, 2021; Yu *et al.*, 2023). Although these studies have examined consumer attitudes toward AI recommendations, relatively less attention has been paid to examining how the characteristics of a product, which play a crucial role in shaping individuals' decision making (Inman *et al.*, 2009), may influence the acceptance of AI recommendations. To address this gap and respond to previous studies on the mixed findings regarding AI recommendation preference, the current research examines how to improve consumers' acceptance of AI recommendations from the perspective of product type.

We choose to focus on experiential versus material products since the topic has attracted significant attention from researchers in the domains of social and consumer psychology (Gilovich and Gallo, 2020), suggesting one of the most widely used product categorizations for capturing consumers' interests (Goodman *et al.*, 2019; Lin *et al.*, 2018). Experiential purchases refer to the purchase of events or experience that a consumer lives through, such as a trip, a movie, or gym membership; while material purchases refer to tangible objects that are kept in one's possession (Van Boven and Gilovich, 2003). Prior research has shown an experiential advantage in various contexts, such as the influence of uncertainty (Gallo *et al.*, 2019), the impact of word of mouth (Bastos and Moore, 2021), and different styles of decision making (Pchelin and Howell, 2014; Tully *et al.*, 2015). However, there remains a dearth of research on how different types of recommendations (AI vs human) influence consumers' attitudes toward experiential/material products.

This study endeavors to fill this gap by investigating whether the impact of AI (vs human) recommendations varies depending on different product types (experiential vs material products). Based on mind perception theory (Gray *et al.*, 2007), we propose that people tend to perceive that AI recommendations are less competent in sense and feel than humans, thus less convincing in recommending experiential products. However, people think that AI recommendations have the capacity to reason and perform objective tasks, thereby endowing them with a greater level of competence in recommending material products than humans.

Through a field experiment and three online/lab experiments, our findings demonstrate that people prefer AI (vs human) recommendations when purchasing material products, but prefer human (vs AI) recommendations when purchasing experiential products. This effect occurs because people hold different competence perceptions regarding AI and human recommendations when choosing these two types of products. However, we find that for experiential purchases, when AI recommendations are used as an assistant rather than a replacement for human recommendations, people's negative attitudes toward AI recommendations may be mitigated.

This study is both theoretically and practically impactful. First, it relates to research on human-technology interaction (Mahlke and Minge, 2008; Grove and Meehl, 1996) by providing a more thorough understanding of the factors promoting AI usage. Second, it extends the literature on experiential versus material purchases (Gilovich and Gallo, 2020) by providing evidence of systematic differences in how people make decisions about AI (vs human) recommendations when evaluating experiential/material products. Third, it contributes to competence perception in assessing the attribute value of AI recommendation in different situations. Practically, our findings shed light on how firms can strategically arrange marketing promotions according to consumers' acceptance of AI recommendations for different types of products.

2. Theoretical framework

2.1 AI recommendations

Ever since the seminal work on statistical predictive models (Grove and Meehl, 1996), a large stream of research has shown interest in artificial intelligence (AI). Based on existing research, AI can be conceptualized as an ecosystem containing three fundamental elements—data collection and storage, statistical techniques, and output systems—that enable products and services to perform tasks typically understood as requiring intelligence and autonomous decision making on behalf of humans (Agrawal *et al.*, 2018). For example, TripAdvisor gives suggestions based on browsing history. Finally, output systems produce a response or communicate with consumers, for example by interacting with a vehicle through consumer interfaces like NAO.

In our research, AI recommendation refers to a technology that utilizes machines, including computer programs and algorithms, to simulate various cognitive processes, such as human perception, learning, cognition, reasoning, decision-making, and interactions for making recommendations (Longoni *et al.*, 2019, 2020). Extant research has shown that AI can make more accurate and efficient judgments than humans in diverse fields such as complex disease diagnosis (Simonite, 2014), market demand forecasting (Sanders and Manrodt, 2003), staff performance evaluation (Kuncel and Beatty, 2013), provision of legal advice (Kleinberg *et al.*, 2018), employment (Braganza *et al.*, 2021; Kim and Heo, 2021).

Existing research has demonstrated that consumers perceive AI and human decision makers to have different strengths and weaknesses. For instance, compared with humans, algorithms are perceived as more objective but also as less authentic, less intuitive, and less moral (Jago, 2019; Yeomans *et al.*, 2019). To illustrate, human agents are able to incorporate considerations of uncertainty (Grove and Meehl, 1996) and people's uniqueness (Longoni *et al.*, 2019). Moreover, human possess pivotal distinguishing qualities, encompassing inherent human intuition (Yeomans *et al.*, 2019), the aptitude to expound upon decision rationales, and the expression of self-confidence (Fernandes and Oliveira, 2021). In domains such as book, movie, and joke recommendations, consumers tend to place greater reliance on humans as opposed to computerized recommendation systems (Yeomans *et al.*, 2019). Yet, given the increased prominence of AI recommendation in curating our experiences, the inquiry arises naturally concerning how well recommender systems perform in comparison to human recommenders. We summarize the relevant studies from recent years in Table 1.

Extant research focuses on numerous reasons that people resist algorithmic recommendations. Individuals tend to exhibit a lack of faith in AI's ability to learn and improve itself (Highhouse, 2008). When facing complex tasks, people are hesitant to take responsibility themselves, and tend to delegate it to other humans rather than relying on AI, apparently due to algorithms' lack of autonomy and strict logical design, rendering them incapable of handling complex tasks (Promberger and Baron, 2006; Reich *et al.*, 2023). Moreover, consumers often consider themselves to be unique individuals facing unique decision-making tasks. As AI solutions tend to be homogeneous, consumers believe that AI cannot effectively solve their individualized problems, resulting in a reluctance to rely on it (Longoni *et al.*, 2019). Lastly, in many consumption contexts, interpersonal interaction is just as important as decision-making efficiency, and the level of interaction serves as a key differentiating factor among similar products. The lack of warmth and empathy displayed by AI has been seen a major reason for people's reluctance to choose it as an option (Grove and Meehl, 1996).

To extend previous research, the current study investigates when consumers are more likely to adopt an AI recommendation. Specifically, we focus on how the characteristics of products (material vs experiential) influences individuals' attitudes towards various recommendation sources.

2.2 Material products and experiential products

In general, most products possess a combination of material and experiential characteristics (Giaccardi and Karana, 2015), but consumers may categorize a product as either an experiential product or as a material product based on their purposes for its use. Material products are typically those purchased with the intention of acquiring a physical object, while

Studies	IV	DV	Main findings
Promberger and Baron (2006)	Medical recommendation: physician vs computer program	Inclination to follow the recommendation	Subjects are more likely to follow a recommendation that came from a physician than from a computer program
Önkal *et al.* (2009)	Financial forecast: human expert vs statistical forecasting method	Forecast adjustments	Participants are more likely to adjust forecasts apparently from a human expert
Diab *et al.* (2011)	Employee selection: structured interview vs mathematical test	Perceived usefulness; perceived legality	Participants from outside the United States prefer holistic integration of interview scores, but slightly prefer mechanical integration of test scores
Eastwood *et al.* (2012)	Legal and medical decision making: fully rational versus heuristic	Preference; accuracy; fairness; ethicalness; and perceived similarity	Clinically based strategies tend to be rated higher than actuarially based strategies, and fully rational strategies were always rated higher than heuristic-based strategies
Dietvorst *et al.* (2015)	Forecast: human vs statistical algorithm	Preference	People are especially averse to algorithmic forecasters after seeing them perform, even when they see them outperform a human forecaster
Dietvorst *et al.* (2016)	Modify model forecast: can't change vs change	Whether or not they choose to use the model's forecasts	Participants are considerably more likely to choose to use an imperfect algorithm when they can modify its forecasts
Logg *et al.* (2019)	Forecasts: human vs algorithm	Weighting advice	Lay people adhere more to advice when they think it comes from an algorithm than from a person; experienced professionals rely less on algorithmic advice than lay people
Yeomans *et al.* (2019)	Jokes recommendation: human vs algorithm	Rating	People are averse to relying on these recommender systems for jokes, but human recommendation
Longoni *et al.* (2019)	Healthcare: AI vs human	Acceptance of AI (vs human) healthcare	Consumers are reluctant to utilize healthcare provided by AI (vs human)
Pantano and Scarpi (2022)	AI vs human	Measurement of AI types and consumer emotions	Artificial intelligence is configurable, describable, and measurable, and influences consumers' positive and negative emotions
Longoni and Cian (2022)	Product type: utilitarian vs hedonic	Preference	AI recommenders are more competent than human recommenders in the utilitarian realm and less competent than human recommenders in the hedonic realm

Table 1.
Research on consumers' attitudes toward AI

(*continued*)

Studies	IV	DV	Main findings
Ahn *et al.* (2022)	Gender of AI (male vs female)	Persuasion effect of AI's recommendation	Participants showed more positive attitudes toward the AI recommendations when the male AI recommended a utilitarian (vs hedonic) product. Conversely, a hedonic product was evaluated more positively when advised by the female (vs male) AI agent
Yalcin *et al.* (2022)	Algorithms vs human	Consumers' reactions to decisions	Compared to managers' predictions, consumers react less positively when a favorable decision is made by an algorithmic (vs a human) decision maker, whereas this difference is mitigated for an unfavorable decision. The effect is driven by distinct attribution processes: it is easier for consumers to internalize a favorable decision outcome that is rendered by a human than by an algorithm, but it is easy to externalize an unfavorable decision outcome regardless of the decision maker type.
Himmelstein and Budescu (2023)	Forecasting advice: human vs algorithmic	Preference	Judges report domain-specific preferences, preferring human advice in the domain of politics and algorithmic advice in the domain of economics
Reich *et al.* (2023)	AI vs human	Taking advice	Consumers tend to avoid algorithmic advice on the often faulty assumption that those algorithms, unlike their human counterparts, cannot learn from mistakes
Snijders *et al.* (2023)	AI vs human	Fake news detection	Confidence has a negative effect on the willingness to accept and request algorithmic advice
Tarafdar *et al.* (2023)	Human–algorithm interactions	Work performance	While the algorithm records all of the human's task actions, it is ignorant of the human's cognitive reactions
Gaczek *et al.* (2023)	AI vs human	Willingness to follow	Consumers are less willing to follow a medical recommendation from AI (vs from a human) when the medical diagnosis provides health results that are good (i.e. symptoms do not require medical care) versus bad (i.e. symptoms are worrisome and may require urgent care)

(*continued*)

Table 1.

Studies	IV	DV	Main findings
Current research	Recommendation type: human vs AI	Acceptance of recommendation	People perceive AI recommendations as more competent than human recommendations for material products, but believe human recommendations are more competent than AI recommendations for experiential products

Table 1.

Source(s): Authors own work

experiential products are purchased with the intent of gaining a particular experience (Van Boven and Gilovich, 2003). Though consumers may not always be able to accurately differentiate between these two product categories, they generally possess a consistent intuition (Gilovich and Kumar, 2015; Gilovich and Gallo, 2020).

Previous research comparing experiential and material purchases has mainly focused on understanding the downward outcomes of these two types, such as happiness (Van Boven and Gilovich, 2003), satisfaction (Carter and Gilovich, 2010), regret (Rosenzweig and Gilovich, 2012), and how they impact interpersonal relationships (Chan and Mogilner, 2017). Another stream literature has largely focused on the factors that influence consumers' preferences for these purchases (Wilson and Merrie, 2017; Rosenzweig and Gilovich, 2012; Kumar and Gilovich, 2015). For example, consumers with higher social status and fewer financial constraints are more likely to prefer experiential products, while those with lower social status and greater financial constraints tend to prefer material products, perhaps due to heightened emphasis on risk factors. Furthermore, sharing an experience with others through the purchase of experiential products enhances people's happiness in the purchase, promotes social relations (Howell and Guevarra, 2013), and strengthens a sense of self-connection, while memories associated with these experiences are more likely to be embellished over time, thereby promoting identity formation (Carter and Gilovich, 2012; Gilovich and Kumar, 2015). Besides, recent research has demonstrated people show different processing modes of these two types of products. For instance, consumers are more inclined to exert effort to acquire experiential (vs material) purchase, and the findings hold for online as well as offline (Bastos, 2020). However, little attention has been paid to how the experiential and material characteristics of products affect consumers' attitudes toward different recommendation sources, especially AI recommendations.

2.3 AI recommendations and product types

Consumers' evaluation of different purchases and product attributes leads to different processing modes (Casado-Aranda *et al.*, 2022). We argue that consumers exhibit divergent attitudes toward AI recommendations that are related to the material and experiential attributes of products. First, when purchasing experiential products characterized by experiential attributes, consumers are required to taste, or feel the product. Hence, the cognitive processing of experiential attributes in the mind may evoke emotions and imaginations (Brakus *et al.*, 2009). When purchasing material products featured with search attributes, consumers are expected to engage in calculating and evaluation. Moreover, search attributes decrease consumers' concerns regarding potential errors in decision-making, while experiential attributes elicit heightened perceptions of risk (Batra and Sinha, 2000). For instance, consumers can easily judge the functionality of a computer through measurable parameters such as CPU performance, whereas they are unable to verify the quality of a restaurant solely based on descriptive information. Second, material products are subject to evaluation using objective criteria, whereas the assessment of experiences is unique to each individual (Eliashberg and Sawhney, 1994), making it more difficult for consumers to compare among different options (Carter and Gilovich, 2010; Gilovich and Kumar, 2015; Gilovich *et al.*, 2015; Holbrook and Hirschman, 1982). For instance, two consumers purchasing the same coffee-making course may have entirely different subjective experiences, while purchasing the same model of coffee maker would result in obtaining products with the same level of performance.

According to the mind perception theory, people are inclined to ascribe mental capacities to other entities based on two complementary dimensions: agency and experience (Gray *et al.*, 2007). Agency is related to thinking and executing, and experience is about the mental state related to sensation and feeling (Gray and Wegner, 2010). Following this logic, people hold different beliefs of humans and artificial intelligence (e.g. Waytz and Norton, 2014). Humans have both agency and experience, whereas artificial intelligence are perceived as having basic cognitive ability and lacking feelings and emotion (Kim and Kim, 2013). Therefore, AI is less capable in evaluating experience which is based on feeling and emotion but can be competent in evaluating tasks based on facts and rationality.

Combined with the discussions of different product types and mind perception theory, we speculate that people's belief in capability of humans/AI and the different information processing required when evaluating material and experiential products may impact the attitudes toward AI and human recommendations. The function of AI is to correctly interpret external data, acquire knowledge via sophisticated algorithms, and achieve specific goals and tasks using the knowledge (Haenlein and Kaplan, 2019). This process operates through rational and rigorous logic programs, which is in line with the information processing of material products, featuring search attributes. In contrast, recommendations by humans are characterized by experience and agency, enabling them to respond to novel queries and generate innovative solutions, which is critical when purchasing experiential products, highlighting experience attributes. More importantly, humans possess the capacity for emotional responsiveness and immediate, effective interactions with their environment and fellow humans, which is currently unavailable to AI systems. For example, a robot may function as a substitute for a waiter in serving food, but it is unable to attend to customers' emotional states or offer timely responses to ensure their satisfaction. Therefore, we hypothesize:

H1. For material products, people hold a more favorable attitude towards AI recommendations (vs human recommendations); for experiential products, people hold a more favorable attitude towards human recommendations (vs AI recommendations).

When making purchase decisions, consumers engage in evaluating the efficacy of the recommendations presented to them, basing their evaluations on a range of indicators such as price, personal preferences and country of origin. As aforementioned, we propose that people believe AI recommenders to be more (less) competent to assess material (experiential) products. These predictions rest on the assumption that people believe material and experiential products require different evaluation competences. When evaluating material products, consumers pay attention to factual, rational, and logical dimensions. However, when evaluating experiential products, they care about emotional and sensory evaluative dimensions. Due to the differential perception of the competencies possessed by AI and human agents in the evaluation of information, along with different evaluative modes when assessing material versus experiential products, people are likely to perceive AI and human recommendations as having different levels of competence in the evaluation of these two types of products. This perception can subsequently influence individuals' attitudes towards recommendations generated by either AI or human agents. Put formally:

H2. Competence perception mediates the relationship between product type and AI recommendations. People believe AI recommenders are more competent than human recommenders when purchasing material products. However, people believe human recommenders are more competent than AI recommenders when purchasing experiential products.

If competence perception serves as a mediator between recommendation type and product type, improving the relative disadvantages of AI recommendations in experiential products would attenuate this effect. According to current practice, AI plays two important roles. That is, AI functions as an assistant, or AI replaces humans to do some tasks. For example, the smart mirrors in dressing rooms employed by Minkoff stores conduct real-time analysis on data from multi-dimensions (Grewal *et al.*, 2020), such as customer portrait and individual product attention, to assist marketing departments in achieving rapid, intelligent, and precise business decisions regarding product selection, display, and promotion. In our context, AI's replacing humans means that AI recommendations completely replace human recommendations (Araya, 2019). Therefore, we hypothesize:

H3. When AI recommendations are utilized as a supplement to human recommendations, consumers will react positively to AI recommendations even for experiential products.

3. Research methodology

We use a variety of experimental scenarios, products, and participants to examine our hypotheses. The pilot study is a field experiment, providing initial evidence that consumers prefer AI recommendation when the purchase is framed as material (vs experiential). Study 1 further investigates how different product types influence consumers' attitudes towards recommendations generated by AI or humans in a controlled setting. Study 2 and Study 3 utilize online experiments to examine the mediating role of competence perception and how different roles that AI plays may moderate the proposed effect. We applied the same exclusion criteria across studies (Table 2). The sample size was determined before each study and all experimental conditions and measures are reported (detailed stimuli in the Appendix). A schematic of our conceptual model along with how each study supports the model is illustrated in Figure 1.

3.1 Pilot study: field experiment

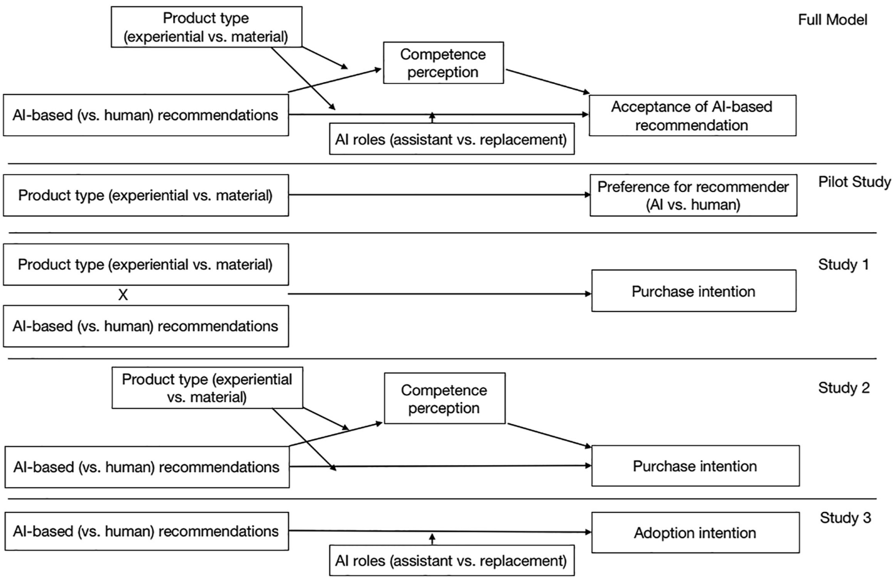
The purpose of this pilot study was to test the hypothesis in a real consumption context, wherein consumers exhibit a preference for AI-based recommendations when faced with material products and for human recommendations in the case of experiential products. To achieve this, we manipulated product type by instructing participants to focus on different aspects of the same product, following the methodology proposed by Dai *et al.* (2020).

3.1.1 Procedure. We cooperated with a chain hair salon located in a county in northern China. The experiment period was from January 21, 2021 to February 4, 2021. The reason for selecting this time period was proximity to the Lunar New Year, when more customers seek hair styling services. Based on preliminary discussions, the experimental period coincided with the salon's business hours (10:00AM-10:00PM) every day. Four staff members were

Table 2. Samples and attention check question

Study	Type of study	Data source	Sample size Final N (initial N)	Measured mediator	Moderator	DV	Attention check question	Findings
Pilot study	field experiment	Hair salon	103 (103)			Preference for recommender	–	When people are instructed to focus on the material (experiential) aspect of the consumption, they are more likely to choose an AI (human) recommender
Study 1	online experiment	MTurk	222 (240)			Purchase intention	What is the accuracy rate of AI-based/human recommendations?	People are more likely to purchase the product when the recommender is AI (human) and the product is material (experiential)
Study 2	online experiment	Credamo	235 (240)	Competence perception		Purchase intention	This item is to check whether you answer carefully, please choose strongly disagree	people perceive AI recommendations as more competent than human recommendations for material products, whereas they believe human recommendations are more competent than AI recommendations for experiential products
Study 3	online experiment	WJX.cn	230 (240)		AI roles (assistant vs replacement)	Adoption intention	Which platform makes the recommendation for you?	Utilizing AI as an assistant for human recommendations on experiential products can reduce the negative attitude people hold towards AI

Source(s): Authors own work



Source(s): Authors own work

Figure 1.
Conceptual model with associated studies and context

recruited to participate in our experiment, including one receptionist and three hair designers. To eliminate the potential influence of hair designers' expertise level, popularity, and service price, the three hair designers participating in the experiment were all chief designers in the salon. To avoid long-time waiting and crowdedness during this period, each customer made an appointment online in advance and arrived at the salon according to their scheduled time.

The experiment involves a 2-cell between-subjects design where customers were instructed to focus on the material aspect or experiential aspect. When customers entered the hair salon, we handed a leaflet explaining that we were conducting a blind test for products in the haircare industry. Then, the receptionist randomly selected one of the two promotional leaflets that were prepared in advance to hand to the customer (Figure 2). In the

Source(s): Authors own work

Figure 2.
Leaflet in the pilot study

condition activating customer's material concern, the leaflet reads "Come to A Tie Style to protect your beautiful hair." In the condition activating customer's experiential concerns, it reads "Come to A Tie Style for a comfortable experience".

If the customers had no clear preference for a particular hair designer, one of the hair designers would inquire about their requirements. To eliminate the potential influence of the presentation order of the two recommendation types, the staff were instructed to randomly present either AI or human recommendations. In the scenario where the AI recommendation was presented first, the hair designer would show the customer the Hair Cool APP and told them it is an AI hairstyling recommendation application. They could put their face in the box and select the desired hairstyle, and the app would generate a design. In the scenario where the human recommendation was presented first, the hair designer would recommend their own design and show it through the app. Each recommender recommended one hairstyle. Finally, the customer decided whether to choose the AI recommendation or the hair designer's recommendation.

In this field experiment, a total of 140 customers received services from the three hair designers. Among them, the hair designer recommendation and the AI recommendation were identical for 16 customers, making it difficult to discern the efficacy of either recommendation, so we excluded these customers' data. Additionally, 21 males refused to view the Hair Cool APP and instead requested a simple haircut. Consequently, 103 valid cases (58.3% female, $M_{age} = 25.32$, SD = 12.27) remained for data analysis.

3.1.2 Results. We compared the proportion of people who selected AI-based recommendations with those who chose hair designer recommendations, under two distinct scenarios related to either material or experiential concern. A chi-square test revealed a significant difference between the two groups ($\chi^2(1, N = 103) = 24.91$, $p < 0.001$). When focusing on material aspects, more people chose the AI recommendation (56.6 vs 43.4%; $z = 1.97$, $p = 0.04$); when focusing on experiences, more people chose the hair designer recommendation (90 vs 10%; $z = 6.21$, $p < 0.001$). Additionally, due to the unique time period of the Chinese New Year, it is possible that people may tend to "follow the herd" in hair style, which could have compromised the validity of our findings. We therefore tracked participants' hairstyle data, and the results indicated that of the 103 customers, 29.1% got a perm, 44.7% had a haircut, and 26.2% had some kind of combined consumption (i.e. getting a perm and dying hair, or cutting hair and dying hair). The distribution of choices in the selected sample was comparable to the distribution of the whole sample across this salon, indicating the representativeness of our dataset.

The pilot study provided initial support for our hypothesis that customers tend to choose AI recommendations when we instructing them to focus on the material aspect. Although the field experiment has ecological validity, the salon's reluctance to disclose customers' personal information led to a lack of data on demographic characteristics, membership status, and consumption amount that may influence the results. Moreover, despite randomized ordering of the recommendation stimuli, the interplay between the two types of recommendations could have produced a spillover effect that affected the results. Lastly, some individual factors were not considered. For example, some consumers may feel curious about, or fear of AI recommendation. Therefore, in the following studies, we adopted more rigorous experimental designs to examine the effects.

3.2 Study 1: main effect

Study 1 had two goals. First, we utilized a different paradigm to manipulate product types. Second, we experimentally tested whether people preferred AI (vs human) recommendations for material (vs experiential) products.

3.2.1 Procedure. 222 participants (M_{age} = 38.89 years, SD = 12.66; 57.7% female) from MTurk were randomly assigned to a 2 (recommendation: AI vs human) × 2 (product type: material vs experiential) between-subjects design. They were paid 22 cents after completing the tasks.

Manipulation of product type. The participants were instructed to buy a coffee maker (material product)/a coffee course (experiential product) and read two posters (Figure 3). The coffee maker was presented as "Bring you a new coffee maker"; the coffee course was depicted as "Bring you a new coffee experience."

Recommendation type. Subsequently, the participants were told that the recommendation was made by AI/an expert. We specified that based on past experience, the accuracy rate of AI/expert recommendations in predicting consumers' preference was up to 99%, and that people's acceptance of AI/expert recommendations was also relatively high. In addition, there would be no interaction with the provider during the process [1].

Purchase intention. Next, we asked about the purchase intention of the participants ("To what extent would you be willing to buy the coffee course/maker recommended by AI/ human recommendations?"; 1 = not at all, 7 = very much; Kim *et al.*, 2021).

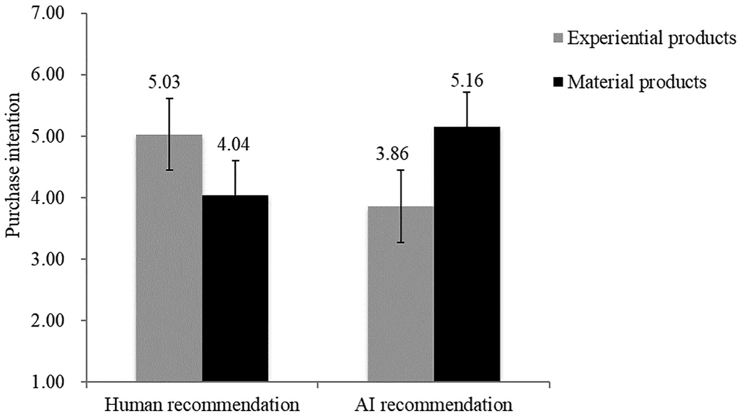
Manipulation check of product types. On the next page of the experiment, we told participants that products can be divided into material products and experiential products based on the why consumers purchase them: experiential products are those purchased to obtain experience, and material products are those purchased to obtain material objects. Then, the participants were asked to indicate to what extent they thought the coffee course/maker was a material product or an experiential product (1 = "purely material," 9 = "purely experiential"). Finally, we asked how much they knew about the coffee maker/coffee course (1 = "not at all," 7 = "very much"). We collected participants' demographic information and thanked them.

3.2.2 Results. ***Manipulation check.*** Results of a one-way ANOVA showed that the participants believed the coffee course was an experiential product (M = 6.01, SD = 2.24), and the coffee maker was a material product (M = 4.86, SD = 2.75; F(1, 220) = 11.75, $p < 0.01$).

Purchase intention. The results of the two-way ANOVA, with product type and recommendation type as independent variables, and purchase intention as the dependent variable, suggested that the main effects of product type (F(1, 218) = 0.29, p = 0.59) and recommendation type (F(1, 218) = 0.01, p = 0.93) were not significant, but their interaction effect was significant (F(1, 218) = 14.89, $p < 0.01$, $\eta^2 = 0.06$). Planned contrast analysis revealed that people were more willing to purchase material products recommended by AI (vs human) (M = 5.16, SD = 2.07; M = 4.04, SD = 2.37; F(1, 218) = 6.45, p = 0.01, $\eta^2 = 0.03$). For experiential products (M = 5.03, SD = 2.00), people's purchase intention following human recommendations was significantly higher than that for AI recommendations (M = 3.86, SD = 2.36; F(1, 218) = 8.67, $p < 0.01$, $\eta^2 = 0.04$, Figure 4). Results still held when we added participants' knowledge about the coffee course/coffee maker as a covariate (F < 1 for the covariate).

Source(s): Authors own work

Figure 3.
Descriptions of coffee course and coffee maker



Source(s): Authors own work

Figure 4. The interaction effect of recommendation type and product type

3.3 Study 2: underlying mechanism

Study 2 aimed to test the underlying mechanism of competence perception. In addition, we highlighted the experiential or the material aspect of the same product, and made the products more experiential or more material focused, to provide a clean test of our proposal.

3.3.1 Procedure. 235 students (Mage = 22.92 years, SD = 2.93; 51.5% female) from the online platform Credamo (www.credamo.com), which has been used by both American researchers and researchers from other cultures (e.g. Yang *et al.*, 2019), participated in this experiment, with each paid 2 RMB after completing the tasks. They were randomly assigned to a 2 (recommendation: AI vs human) × 2 (product type: material vs experiential) between-subjects design. Before the experiment, the participants were instructed to imagine that they were going to buy a pair of shoes but had not yet decided which one to buy and would get recommendations on a particular type of platform.

Recommendation type. In the condition of the AI recommendation, participants were informed that the platform employed advanced algorithms to generate recommendations for consumers. In condition of the human recommendation, participants were informed that the platform employed sneaker experts to provide recommendations for consumers.

Manipulation of product type. Following previous research (Van Boven and Gilovich, 2003), we manipulated product type by framing the same product either in material or in an experience. Participants were presented with a picture of a pair of sneakers suitable for either gender (Figure 5). For material products, the promotional slogan was

Source(s): Authors own work

Figure 5. Stimuli of study 2

"New high-tech running shoes, with green technology using natural materials. Bring you professional sports equipment." For experiential products, the slogan was "New comfortable running shoes, with green technology giving a breathable experience. Allow you to fully enjoy sports."

Purchase intention. Next, we asked the participants about their purchase intention ("To what extent would you be willing to buy the sneakers recommended by AI/human recommendations?"; 1 = "not at all," 7 = "very much"; Kim *et al.*, 2021).

Competence perception. To test the underlying mechanism, we asked the following questions on another page of the experiment: "To what extent do you think AI/sneaker experts can select an appropriate pair of sneakers?" and "To what extent do you think AI/ sneaker experts can do a good job in recommending an appropriate pair of sneakers?" (1 = "not at all," 7 = "very much"; $r = 0.79$; Longoni *et al.*, 2020).

Manipulation check of product type. Similar to Study 1, participants were asked to indicate to what extent they thought of the sneakers as a material product or an experiential product (1 = "purely material," 7 = "purely experiential").

Subsequently, we asked participants about the attractiveness of the sneakers, how much they loved the sneakers and to what extent they thought buying the sneakers was an important decision (1 = "not at all," 7 = "very important"). Finally, we collected the participants' demographic information and thanked them.

3.3.2 Results. ***Manipulation check.*** Results of a one-way ANONA showed that the product types were manipulated successfully. In material condition, participants thought the sneaker was a material product (M = 5.07, SD = 1.46); in the experiential condition, they perceived the sneaker as an experiential product (M = 6.54, SD = 1.08; $F(1, 230) = 7.89$, $p < 0.01$).

Purchase intention. Results of the two-way ANOVA with product type and recommendation type as independent variables, and purchase intention as the dependent variable showed a significant interaction effect of product type and recommendation type ($F(1, 231) = 22.08$, $p < 0.01$). Neither the main effect of recommendation type ($F(1, 231) = 0.23$, $p = 0.63$) nor the main effect of product type was significant ($F(1, 231) = 0.03$, $p = 0.88$). Further, a planned contrast revealed that for material products, participants were more likely to purchase those recommended by AI (M = 5.24, SD = 1.50) rather than by a human expert (M = 4.08, SD = 1.91; $F(1, 231) = 14.56$, $p < 0.01$). For experiential products, participants were more likely to purchase those recommended by a human expert (M = 5.16, SD = 1.51) than by AI (M = 4.23, SD = 1.85; $F(1, 231) = 8.25$, $p < 0.01$).

Competence perception. Results of the two-way ANOVA with product type and recommendation type as independent variables, and purchase intention as the dependent variable showed a significant interaction effect of product type and recommendation type ($F(1, 231) = 12.99$, $p < 0.01$). Neither the main effect of recommendation type ($F(1, 231) = 0.14$, $p = 0.71$) nor the main effect of product type was not significant ($F(1, 231) = 0.96$, $p = 0.33$). Planned contrast analysis showed that for material products, participants thought AI (M = 5.18, SD = 1.42) was more competent than a human expert (M = 4.54, SD = 1.48; $F(1, 231) = 12.99$, $p = 0.02$). For experiential products, participants were thought a human expert (M = 5.06, SD = 1.46) was more competent than AI (M = 4.27, SD = 1.72; $F(1, 231) = 7.34$, $p < 0.01$).

Moderated mediation. We used PROCESS model 8 (sample size: 5,000, Hayes, 2018) to test whether the different effects of AI recommendations in different product types work through competence perception. This model accommodated a moderating effect preceding the mediating variable. The interaction effect between product type and recommendation type was significant (95% CI [0.28, 1.14]). As hypothesized, the indirect effect of recommendation type → competence perception → purchase intention was significant, but its influence on experiential products (95% CI [0.09, 0.73]) and material products (95% CI [−0.57, −0.06]) was in opposite directions.

3.4 Study 3: moderating effect of AI role

Study 3 tested the different roles of AI as a boundary condition. We proposed that utilizing AI as an assistant for human recommendations regarding experiential products could reduce the negative attitude people hold towards AI. Moreover, to further distinguish between AI and human recommendations, a control group was included in this study.

3.4.1 Procedure. 230 participants (M_{age} = 27.5 years, SD = 11.5; 42.1% female) from a large online consumer panel (WJX.cn) were randomly assigned to a between-subjects design with 4 conditions (human recommendations vs AI recommendations vs AI assistant vs control group). They were paid 5 RMB after completing the tasks. Consistent with previous research (Dai *et al.*, 2020), we chose tourism as a typical experiential consumption category. Participants were asked to imagine they were planning a two-day trip to Xiamen, a city in China, and had no prior knowledge of the area. To generate ideas for their trip, they were directed to browse the Mafengwo website. The website provided participants with two types of recommendations, which were generated by AI or by the company's customer service. The two types of recommendations were based on the same database of past consumer comments, sharing, and metrics such as number of reads and likes. Next, participants were randomly assigned to receive recommendations from human customer service staff, AI, or a combination of both in the form of an AI assistant (Figure 6). The control condition entailed no recommender manipulation. Instead, participants only saw the description of the route. Specific information is as follows:

[Human recommendation group] The customer service staff Yangyang will provide you with service. Yangyang will provide you with route recommendation service throughout the process.

[AI recommendation group] The AI assistant Xiao A will provide you with service. Xiao A will provide you with route recommendation service throughout the process.

[AI as assistant group] The AI assistant Xiao A and the customer service staff Yangyang will work together to provide you with service. AI Xiao A will first provide you with a preliminary plan based on our database, and then Yangyang will make the final recommendation decision for you.

Subsequently, participants proceeded to the following page where they were presented with recommended tourist routes.

Adoption intention. Next, we asked the participants about their willingness to adopt the tourist route (1 = "not at all," 7 = "very much").

We then asked for their perception of the complexity of the task of developing a tourist route (1 = "not at all," 7 = "very complex"). Finally, we collected demographic information.

3.4.2 Results. Results of the one-way ANOVA were consistent with our hypothesis and showed significant differences among the four groups ($F(3, 226) = 14.17$, $p < 0.01$). Planned contrast analyses revealed that participants had a higher intention to adopt a tourist routes recommended by a human source (M = 4.95, SD = 1.76), compared to AI (M = 3.25, SD = 1.63; $t(226) = 5.71$, $p < 0.01$). However, when AI played an assistant role, participants' intention to adopt the AI recommendation (M = 4.89, SD = 1.57) was similar to their intention to adopt the human recommendation ($t(226) = 0.18$, $p = 0.86$) and higher than that to adopt the AI recommendation ($t(226) = 5.50$, $p < 0.01$). The control group's intention (M = 4.29, SD = 1.41) was slightly lower than that of the human recommendation group ($t(226) = 2.21$, $p = 0.03$), but higher than the AI recommendation group ($t(226) = 3.54$, $p < 0.01$). There were no significant differences between the control group and the AI assistant group ($t(226) = 2.01$, $p = 0.05$). Perception of the complexity of the task of developing a tourist route did not significantly differ among the four groups ($F(3, 226) = 0.88$, $p = 0.45$; Figure 7). Results of Study 3 demonstrated that even for experiential products, people's reluctance regarding AI can be reduced when AI plays an assistant role.

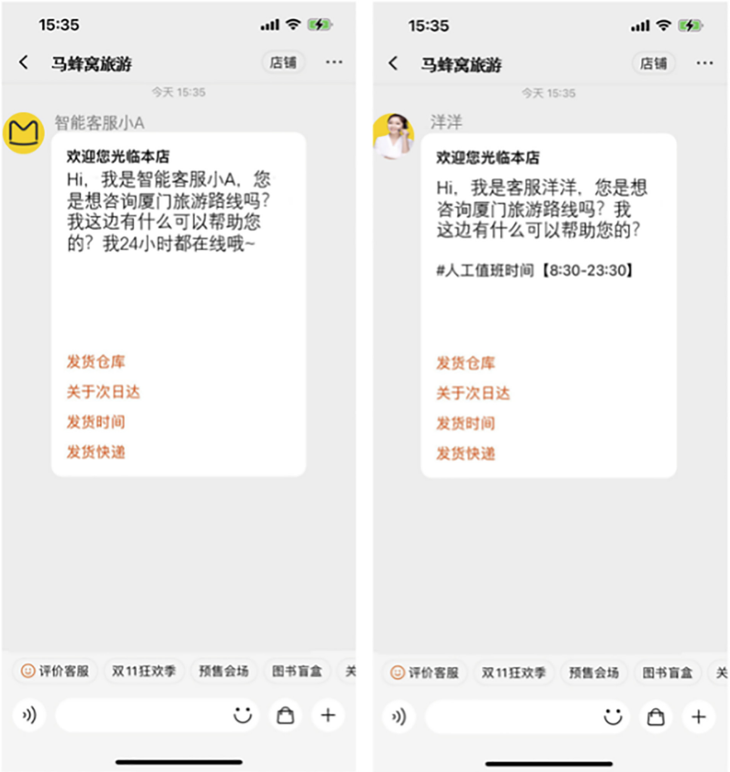


Figure 6.
Stimuli of study 3

Source(s): Authors own work

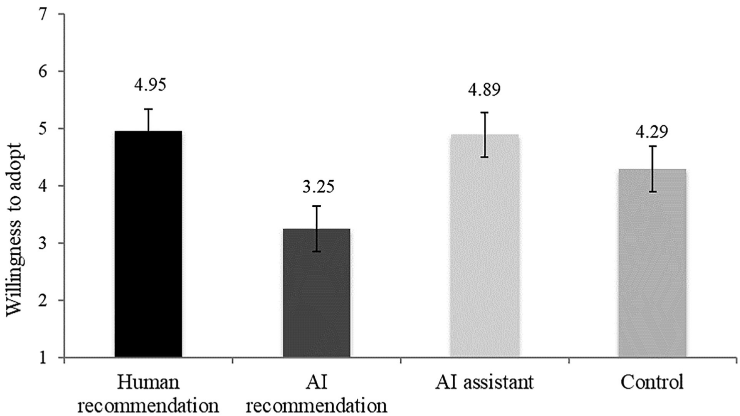


Figure 7.
Intention to adopt between different conditions

Source(s): Authors own work

4. Conclusion

With the development of science and technology, AI products and services are becoming an integral part of life, transforming the way consumers make decisions. For example, ModiFace has announced that it will provide its AI-powered technology to enable the first virtual try-ons for cosmetics on Amazon. Travel reservation giants like Booking.com, Skyscanner, and Expedia are using chatbots in their operations to find consumers the best deal. These technological advances suggest that the development of statistical/actuarial models have made AI algorithms more intelligent, faster, and convenient (Bohn *et al.*, 2019). Yet despite many examples of AI algorithms' performing better than humans in predicting many events, such as students' and employees' performance (Dawes, 1979) and market demand (Sanders and Manrodt, 2003), people often remain cautious about considering AI recommendations.

The current research explored how to improve consumers' acceptance of AI recommendations from the perspective of product type (material vs experiential products). Using a field experiment and three online experiments, we found that when purchasing experiential products, people tended to prefer recommendations from humans over AI, whereas when purchasing material products, people preferred AI recommendations over those from humans (Pilot Study and Study 1). This result occurred because people had different competence perceptions of different recommendation types when they purchase different products (Study 2). Additionally, we found that people's negative attitudes toward AI recommendations were reduced when AI played an assistant role rather than replacing humans in recommending experiential products (Study 3).

4.1 Theoretical implications

Our research provides three theoretical contributions. First, it enriches the research on AI and human-machine interaction (Mahlke and Minge, 2008; Grove and Meehl, 1996; Longoni and Cian, 2022). Previous studies have focused mostly on "algorithm aversion" (e.g. Longoni *et al.*, 2019, 2020; Highhouse, 2008). However, this paper explores people's different attitude towards AI recommendations from the perspective of product type (material vs experiential products), indicating a way of improving acceptance to AI recommendations. Our findings suggest that while people exhibit a positive inclination towards AI recommendations for material products, they prefer human recommendations for experiential products. Thus, our study is a valuable response to extant research calling for in-depth scrutiny of ways to increase acceptance to AI (Araya, 2019), as no prior studies have delved into the influence of products' material and experiential attributes on consumers' attitudes towards AI recommendations.

Second, our research expands the literature on material products and experiential products (Gilovich and Gallo, 2020). Existing studies have investigated primarily the factors influencing consumers' choice between the two product types, such as social class (Lee *et al.*, 2018), financial situation (Tully *et al.*, 2015), and information processing fluency (Brakus *et al.*, 2014). Our study reveals that people's different concerns regarding the material and experiential attributes of products can significantly influence their attitudes towards various recommendation sources, thereby contributing to the post-outcome variable of different product types. Additionally, while prior research has examined the effect of different forms or content of online reviews for experiential and material purchases (Dai *et al.*, 2020), our study shifts to a source effect with a specific emphasis on the emerging source of AI.

Third, our research further reveals under what circumstances people think AI has higher competence (Longoni and Cian, 2022). Prior studies have explained why consumers resist AI from the perspective of uniqueness neglect (Longoni *et al.*, 2019). Some studies have also found that people who do not rely on AI hold an inherent belief that, unlike humans, AI does not reflect or learn from mistakes (Dietvorst *et al.*, 2015). Additionally, some studies have explored the circumstances that foster preference for AI, such as when AI caters to people's unique needs (Longoni *et al.*, 2019), when the degree of personalization increases (Fan *et al.*, 2022), and when human beings can exert control over AI (Dietvorst *et al.*, 2016). Our research further unveils that when AI serves as an assistant rather than a replacement, people exhibit positive attitudes towards AI recommendations even for experiential products.

4.2 Managerial implications

Our results also have managerial implications for businesses and marketing managers. First, our research can offer practical guidance to enterprises for the more effective use of AI recommendations. For example, Sephora employs both sales staff and AI recommendations (Nguyen *et al.*, 2022). Such an approach, based on product characteristics, can enhance the efficacy of the recommendations, in that our research suggests that the former is preferable for products with distinct experiential features, and the latter for products with obvious material attributes. This leads to a higher level of consumer satisfaction, thereby creating win-win beneficial outcomes for both business and consumers.

Second, our results apply to marketing communications. Managers could communicate to their customers in a way that is aligned with a target segment's goal (i.e. gaining an object vs gaining an experience) and emphasize the most effective points of parity/difference with competing brands or across different products in the portfolio.

Third, our study can offer valuable guidance for enterprises involved primarily in material products, such as home appliances. Specifically, for products where material attributes carry significant weight in the eyes of consumers, AI-based recommendations could be used in a targeted way to cater to customers' needs and improve their perception of products' cost-effectiveness and reliability. For products that customers seek for the user experience, sales staff recommendations or personalized AI recommendations in an auxiliary role could be used to provide tailored services. Thus, the human/AI recommendation approach could be leveraged based on product type and the corresponding target audience.

Finally, Study 3 provides a managerial relevant boundary condition: the combination of human and AI recommendations. The results of this study indicate that consumers are more receptive to AI recommenders, even for experiential purchases, if the AI assists rather than replaces a human recommender. These results are important for practitioners managing relatively more experiential products. For instance, in the hospitality industry, practitioners could leverage our results and utilize AI systems to generate an initial recommendation upon which a human could then add a final confirmation to alleviate consumers' concerns.

4.3 Limitations and future directions

This study has several limitations, some of which point to opportunities for future research. First, we showed, from the competence perception perspective, why consumers show different attitudes toward AI when choosing between material and experiential products. However, it is predicted that with the further development of AI, a Super AI will be created that is self-aware and surpasses the capacity of human intelligence and ability (Escott, 2017). Future research could explore whether such AI's perceived creativity and imagination will impact consumers' acceptance. Similarly, this study focused on situations in which consumers knew the recommendation source before choosing products. Future research can examine if consumer satisfaction is affected when the recommendation source is not disclosed before consumers choose products (Davenport *et al.*, 2020).

Second, for the most part this study examined consumers who accepted AI recommendations when choosing material and experiential products. Future research could expand the investigation of the role of AI recommendations in diverse product decision-making contexts. AI-powered technologies may be instrumental in enhancing the customer experience at each phase of the consumer journey by offering products of increasing personalization (Venkatesan and Lecinski, 2021).

Third, the perceived richness of product options may influence the effectiveness of AI recommendations. While this study focuses on recommendations for a single product, in situations where a large number of product options are available, experts may struggle to manage the vast amount of real-time updated content within a limited timeframe due to cognitive limitations. In such a case, consumers might develop a stronger perception of the competence of AI recommendations, rendering them more effective.

To summarize, understanding when people tend to be amenable to or resistant toward AI-driven recommendations is a pressing endeavor for both researchers and firms alike. Our research explores the match effect of AI (vs human) recommendations and material (vs experiential) products, and demonstrates that such effect stems from competence perception. We hope that these findings will spur further exploration of this important topic.

Notes

1. In our experiments, the participants answered the question, "Whether an AI or a human provided the above recommendation for you?" (AI, human), as a manipulation check.

References

Agrawal, A., Gans, J. and Goldfarb, A. (2018), *Prediction Machines: The Simple Economics of Artificial Intelligence*, Harvard Business Press, Boston, Massachusetts.

Ahn, J., Kim, J. and Sung, Y. (2022), "The effect of gender stereotypes on artificial intelligence recommendations", *Journal of Business Research*, Vol. 141, pp. 50-59.

Araya, D. (2019), "3 Things you need to know about augmented intelligence", Forbes, (January 22), available at: https://www.forbes.com/sites/danielaraya/2019/01/22/3-things-you-need-to-know-about augmented-intelligence/

Bastos, W. (2020), "'Speaking of purchases': how conversational potential determines consumers' willingness to exert effort for experiential versus material purchases", *Journal of Interactive Marketing*, Vol. 50 No. 1, pp. 1-16.

Bastos, W. and Moore, S.G. (2021), "Making word-of-mouth impactful: why consumers react more to WOM about experiential than material purchases", *Journal of Business Research*, Vol. 130, pp. 110-123.

Batra, R. and Sinha, I. (2000), "Consumer-level factors moderating the success of private label brands", *Journal of Retailing*, Vol. 76 No. 2, pp. 175-191.

Bohn, B., Rieger, C. and Griebel, M. (2019), "A representer theorem for deep kernel learning", *The Journal of Machine Learning Research*, Vol. 20 No. 1, pp. 2302-2333.

Bonaccio, S. and Dalal, R.S. (2006), "Advice taking and decision-making: an integrative literature review, and implications for the organizational sciences", *Organizational Behavior and Human Decision Processes*, Vol. 101 No. 2, pp. 127-151.

Braganza, A., Chen, W., Canhoto, A. and Sap, S. (2021), "Productive employment and decent work: the impact of AI adoption on psychological contracts, job engagement and employee trust", *Journal of Business Research*, Vol. 131, pp. 485-494.

Brakus, J.J., Schmitt, B.H. and Zarantonello, L. (2009), "Brand experience: what is it? How is it measured? Does it affect loyalty?", *Journal of Marketing*, Vol. 73 No. 3, pp. 52-68.

Brakus, J., Schmitt, B.H. and Zhang, S. (2014), "Experiential product attributes and preferences for new products: the role of processing fluency", *Journal of Business Research*, Vol. 67 No. 11, pp. 2291-2298.

Carter, T.J. and Gilovich, T. (2010), "The relative relativity of material and experiential purchases", *Journal of Personality and Social Psychology*, Vol. 98 No. 1, pp. 146-159.

Carter, T.J. and Gilovich, T. (2012), "I am what I do, not what I have: the differential centrality of experiential and material purchases to the self", *Journal of Personality and Social Psychology*, Vol. 102 No. 6, pp. 1304-1317.

Casado-Aranda, L., Sánchez-Fernández, J. and Viedma-del-Jesús, M. (2022), "Neural responses to hedonic and utilitarian banner ads: an fMRI study", *Journal of Interactive Marketing*, Vol. 57 No. 2, pp. 296-322.

Castelo, N., Bos, M.W. and Lehmann, D.R. (2019), "Task-dependent algorithm aversion", *Journal of Marketing Research*, Vol. 56 No. 5, pp. 809-825.

Chan, C. and Mogilner, C. (2017), "Experiential gifts foster stronger social relationships than material gifts", *Journal of Consumer Research*, Vol. 43 No. 6, pp. 913-931.

Dai, H., Chan, C. and Mogilner, C. (2020), "People rely less on consumer reviews for experiential than material purchases", *Journal of Consumer Research*, Vol. 46 No. 6, pp. 1052-1075.

Davenport, T., Guha, A., Grewal, D. and Bressgott, T. (2020), "How artificial intelligence will change the future of marketing", *Journal of the Academy of Marketing Science*, Vol. 48, pp. 24-42.

Dawes, R.M. (1979), "The robust beauty of improper linear models in decision making", *American Psychologist*, Vol. 34 No. 7, pp. 571-582.

Diab, D.L., Pui, S.-Y., Yankelevich, M. and Highhouse, S. (2011), "Lay perceptions of selection decision aids in US and non-US samples", *International Journal of Selection and Assessment*, Vol. 19 No. 2, pp. 209-216.

Dietvorst, B.J., Simmons, J.P. and Massey, C. (2015), "Algorithm aversion: people erroneously avoid algorithms after seeing them err", *Journal of Experimental Psychology General*, Vol. 144 No. 1, pp. 114-126.

Dietvorst, B.J., Simmons, J.P. and Massey, C. (2016), "Overcoming algorithm aversion: people will use imperfect algorithms if they can (even slightly) modify them", *Management Science*, Vol. 64 No. 3, pp. 1155-1170.

Eastwood, J., Snook, B. and Luther, K. (2012), "What people want from their professionals: attitudes toward decision-making strategies", *Journal of Behavioral Decision Making*, Vol. 25 No. 5, pp. 458-468.

Eliashberg, J. and Sawhney, M.S. (1994), "Modeling goes to hollywood: predicting individual differences in movie enjoyment", *Management Science*, Vol. 40 No. 9, pp. 1151-1173.

Escott, E. (2017), "What are the 3 types of AI? A guide to narrow, general, and super artificial intelligence", available at: https://codebots.com/artificial-intelligence/the-3-types-of-ai-is-the-third-evenpossible

Fan, H., Han, B., Gao, W. and Li, W. (2022), "How AI chatbots have reshaped the frontline interface in China: examining the role of sales-service ambidexterity and the personalization-privacy paradox", *International Journal of Emerging Markets*, Vol. 17 No. 4, pp. 967-986.

Fernandes, T. and Oliveira, E. (2021), "Understanding consumers' acceptance of automated technologies in service encounters: drivers of digital voice assistants adoption", *Journal of Business Research*, Vol. 122, pp. 180-191.

Gaczek, P., Pozharliev, R., Leszczyński, G. and Zieliński, M. (2023), "Overcoming consumer resistance to AI in general health care", *Journal of Interactive Marketing*, Vol. 58 Nos 2-3, pp. 321-338.

Gallo, I., Jampol, L., Rampullo, A. and Gilovich, T. (2019), "Surprise! The positive impact of uncertainty on the evaluation of experiential purchases", Working paper. IESE Business School.

Giaccardi, E. and Karana, E. (2015), "Foundations of materials experience: an approach for HCI", *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, pp. 2447-2456.

Gilovich, T. and Gallo, I. (2020), "Consumers' pursuit of material and experiential purchases: a review", *Consumer Psychology Review*, Vol. 3, pp. 20-33.

Gilovich, T. and Kumar, A. (2015), "We'll always have Paris", *Advances in Experimental Social Psychology*, Vol. 51 No. 1, pp. 147-187.

Gilovich, T., Kumar, A. and Jampol, L. (2015), "A wonderful life: experiential consumption and the pursuit of happiness", *Journal of Consumer Psychology*, Vol. 25 No. 1, pp. 152-165.

Goodman, J.K., Malkoc, S.A. and Rosenboim, M. (2019), "The material- experiential asymmetry in discounting: when experiential purchases lead to more impatience", *Journal of Consumer Research*, Vol. 46 No. 4, pp. 671-688.

Gray, K. and Wegner, D.M. (2010), "Blaming God for our pain: human suffering and the divine mind", *Personality and Social Psychology Review*, Vol. 14 No. 1, pp. 7-16.

Gray, H.M., Gray, K. and Wegner, D.M. (2007), "Dimensions of mind perception", *Science*, Vol. 315 No. 5812, p. 619.

Grewal, D., Hulland, J., Kopalle, P.K. and Karahanna, E. (2020), "The future of technology and marketing: a multidisciplinary perspective", *Journal of the Academy of Marketing Science*, Vol. 48, pp. 1-8.

Grove, W.M. and Meehl, P.E. (1996), "Comparative efficiency of informal (subjective, impressionistic) and formal (mechanical, algorithmic) prediction procedures: the clinical-statistical controversy", *Psychology, Public Policy, and Law*, Vol. 2 No. 2, p. 293.

Haenlein, M. and Kaplan, A. (2019), "A brief history of artificial intelligence: on the past, present, and future of artificial intelligence", *California Management Review*, Vol. 61 No. 4, pp. 5-14.

Hayes, A.F. (2018), "Partial, conditional, and moderated mediation: quantification, inference, and interpretation", *Communication Monographs*, Vol. 85 No. 1, pp. 4-40.

Highhouse, S. (2008), "Stubborn reliance on intuition and subjectivity in employee selection", *Industrial and Organizational Psychology*, Vol. 1 No. 3, pp. 333-342.

Himmelstein, M. and Budescu, D.V. (2023), "Preference for human or algorithmic forecasting advice does not predict if and how it is used", *Journal of Behavioral Decision Making*, Vol. 36 No. 1, p. e2285.

Holbrook, M.B. and Hirschman, E.C. (1982), "The experiential aspects of consumption: consumer fantasies, feelings, and fun", *Journal of Consumer Research*, Vol. 9 No. 2, pp. 132-140.

Howell, R.T. and Guevarra, D.A. (2013), "Buying happiness: differential consumption experiences for material and experiential purchases", *Advances in Psychology Research*, Vol. 98, pp. 57-69.

Huang, M.H. and Rust, R.T. (2021), "Engaged to a robot? The role of AI in service", *Journal of Service Research*, Vol. 24 No. 1, pp. 30-41.

Inman, J.J., Winer, R.S. and Ferraro, R. (2009), "The interplay among category characteristics, customer characteristics, and customer activities on in-store decision making", *Journal of Marketing*, Vol. 73 No. 5, pp. 19-29.

Jago, A. (2019), "Algorithms and authenticity", *Academy of Management Discoveries*, Vol. 5 No. 1, pp. 38-56.

Kim, J.Y. and Heo, W. (2021), "Artificial intelligence video interviewing for employment: perspectives from applicants, companies, developer and academicians", *Information Technology and People*, Vol. 35 No. 3, pp. 861-878.

Kim, M.S. and Kim, E.J. (2013), "Humanoid robots as 'The Cultural Other': are we able to love our creations?", *AI and Society*, Vol. 28, pp. 309-318.

Kim, J., Giroux, M. and Lee, J.C. (2021), "When do you trust AI? The effect of number presentation detail on consumer trust and acceptance of AI recommendations", *Psychology and Marketing*, Vol. 38 No. 7, pp. 1140-1155.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J. and Mullainathan, S. (2018), "Human decisions and machine predictions", *The Quarterly Journal of Economics*, Vol. 133 No. 1, pp. 237-293.

Kumar, A. and Gilovich, T. (2015), "Some 'Thing' to talk about? Differential story utility from experiential and material purchases", *Personality and Social Psychology Bulletin*, Vol. 41 No. 10, pp. 1320-1331.

Kuncel, N.R. and Beatty, A.S. (2013), "Thinking at work: intelligence, critical thinking, job knowledge, and reasoning", *APA Handbook of Testing and Assessment in Psychology*, pp. 417-435.

Lee, J.C., Hall, D.L. and Wood, W. (2018), "Experiential or material purchases? Social class determines purchase happiness", *Psychological Science*, Vol. 29 No. 7, pp. 1031-1039.

Leung, E., Paolacci, G. and Puntoni, S. (2018), "Man versus machine: resisting automation in identity-based consumer behavior", *Journal of Marketing Research*, Vol. 55 No. 6, pp. 818-831.

Lin, R., van de Ven, N. and Utz, S. (2018), "What triggers envy on Social Network Sites? A comparison between shared experiential and material purchases", *Computers in Human Behavior*, Vol. 85, pp. 271-281.

Logg, J.M., Minson, J.A. and Moore, D.A. (2019), "Algorithm appreciation: people prefer algorithmic to human judgment", *Organizational Behavior and Human Decision Processes*, Vol. 151, pp. 90-103.

Longoni, C. and Cian, L. (2022), "Artificial intelligence in utilitarian vs hedonic contexts: the 'word-of-machine' effect", *Journal of Marketing*, Vol. 86 No. 1, pp. 91-108.

Longoni, C., Bonezzi, A. and Morewedge, C.K. (2019), "Resistance to medical artificial intelligence", *Journal of Consumer Research*, Vol. 46 No. 4, pp. 629-650.

Longoni, C., Bonezzi, A. and Morewedge, C. (2020), "Resistance to medical artificial intelligence is an attribute in a compensatory decision process: response to Pezzo and Beckstead (2020)", *Judgment and Decision Making*, Vol. 15 No. 3, pp. 446-448.

Mahlke, S. and Minge, M. (2008), "Consideration of multiple components of emotions in human-technology interaction", *Affect and Emotion in Human-Computer Interaction: From Theory to Applications*, pp. 51-62.

Nguyen, M., Chen, Y., Nguyen, T.H., Habashi, S.S., Quach, S. and Thaichon, P. (2022), "Artificial intelligence (AI)-driven services: communication support, assistance for decision-making, and enhanced customer experience service", *Artificial Intelligence for Marketing Management*, Routledge, pp. 76-95.

Önkal, D., Goodwin, P., Thomson, M., Gönül, S. and Pollock, A. (2009), "The relative influence of advice from human experts and statistical methods on forecast adjustments", *Journal of Behavioral Decision Making*, Vol. 22 No. 4, pp. 390-409.

Pantano, E. and Scarpi, D. (2022), "I, robot, you, consumer: measuring artificial intelligence types and their effect on consumers emotions in service", *Journal of Service Research*, Vol. 25 No. 4, pp. 583-600.

Pchelin, P. and Howell, R.T. (2014), "The hidden cost of value-seeking: people do not accurately forecast the economic benefits of experiential purchases", *The Journal of Positive Psychology*, Vol. 9 No. 4, pp. 322-334.

Promberger, M. and Baron, J. (2006), "Do patients trust computers?", *Journal of Behavioral Decision Making*, Vol. 19 No. 5, pp. 455-468.

Reich, T., Kaju, A. and Maglio, S.J. (2023), "How to overcome algorithm aversion: learning from mistakes", *Journal of Consumer Psychology*, Vol. 33 No. 2, pp. 285-302.

Rosenzweig, E. and Gilovich, T. (2012), "Buyer's remorse or missed opportunity? Differential regrets for material and experiential purchases", *Journal of Personality and Social Psychology*, Vol. 102 No. 2, pp. 215-223.

Sanders, N.R. and Manrodt, K.B. (2003), "The efficacy of using judgmental versus quantitative forecasting methods in practice", *Omega: The International Journal of Management Science*, Vol. 31 No. 6, pp. 511-522.

Simonite, T. (2014), "Google's intelligence designer", *MIT Technology Review*.

Snijders, C., Conijn, R., de Fouw, E. and van Berlo, K. (2023), "Humans and algorithms detecting fake news: effects of individual and contextual confidence on trust in algorithmic advice", *International Journal of Human–Computer Interaction*, Vol. 39 No. 7, pp. 1483-1494.

Tarafdar, M., Page, X. and Marabelli, M. (2023), "Algorithms as co-workers: human algorithm role interactions in algorithmic work", *Information Systems Journal*, Vol. 33 No. 2, pp. 232-267.

Tully, S.M., Hershfield, H.E. and Meyvis, T. (2015), "Seeking lasting enjoyment with limited money: financial constraints increase preference for material goods over experiences", *Journal of Consumer Research*, Vol. 42 No. 1, pp. 59-75.

Van Boven, L. and Gilovich, T. (2003), "To do or to have? That is the question", *Journal of Personality and Social Psychology*, Vol. 85 No. 6, pp. 1193-1202.

Venkatesan, R. and Lecinski, J. (2021), *The AI Marketing Canvas: A Five-Stage Road Map to Implementing Artificial Intelligence in Marketing*, Stanford University Press, Stanford, California.

Waytz, A. and Norton, M.I. (2014), "Botsourcing and outsourcing: robot, British, Chinese, and German workers are for thinking-not feeling-jobs", *Emotion*, Vol. 14 No. 2, pp. 434-444.

Wilson, B. and Merrie, B. (2017), "How and why conversational value leads to happiness for experiential and material purchases", *Journal of Consumer Research*, Vol. 44 No. 3, pp. 598-612.

Yalcin, G., Lim, S., Puntoni, S. and van Osselaer, S.M. (2022), "Thumbs up or down: consumer reactions to decisions by algorithms versus humans", *Journal of Marketing Research*, Vol. 59 No. 4, pp. 696-717.

Yang, X., Mao, H., Jia, L. and Bublitz, M.G. (2019), "A sweet romance: divergent effects of romantic stimuli on the consumption of sweets", *Journal of Consumer Research*, Vol. 45 No. 6, pp. 1213-1229.

Yaniv, I. (2004), "The benefit of additional opinions", *Current Directions in Psychological Science*, Vol. 13 No. 2, pp. 75-78.

Yaniv, I. and Kleinberger, E. (2000), "Advice taking in decision making: egocentric discounting and reputation formation", *Organizational Behavior and Human Decision Processes*, Vol. 83 No. 2, pp. 260-281.

Yeomans, M., Shah, A., Mullainathan, S. and Kleinberg, J. (2019), "Making sense of recommendations", *Journal of Behavioral Decision Making*, Vol. 32 No. 4, pp. 403-414.

Yu, X., Xu, S. and Ashton, M. (2023), "Antecedents and outcomes of artificial intelligence adoption and application in the workplace: the socio-technical system theory perspective", *Information Technology and People*, Vol. 36 No. 1, pp. 454-474.

(The Appendix follows overleaf)

Appendix

Instruction of Study 2

In this survey, we want to understand people's preference. Your participation will take about 1 minutes. Your participation in this study is voluntary.

You are free to withdraw from the study without any penalty to you. Your data will be kept completely confidential and no personally identifiable information will be collected.

There are no risks involved in this study other than what you would encounter in daily life.Potential benefits to you include receiving information about the outcomes of the study as well as references to related research if you are interested.

Your data will remain completely anonymous and will not be released in any way that can be linked to you. Data from this study will be kept locked or password-protected, and will be destroyed when no longer needed for research purposes.

○ I declare that my consent is voluntary, and that I have read and understood all of the above.

Items in Study 1

Purchase intention.
To what extent would you be willing to buy the coffee course/ maker recommended by AI/human recommendations? (1 = "not at all,"7 = "very much"; Kim *et al.*, 2021).

Manipulation check of product type.
To what extent do you think the coffee course/ maker was a material product or an experiential product? (1 = "purely material," 9 = "purely experiential").

Instruction of Study 2

亲爱的同学：
你好！我们是[illegible]商学院消费行为研究课题组的成员。现在想针对消费者日常决策进行一项调查。该调查没有标准答案，也不涉及对错，所有的结果也只以汇总的形式用于学术分析，请放心填写。认真完成了此项调研，您将获得**2元**的报酬作为对您时间和精力的补偿。报酬将在完成调查后48小时内，通过平台红包发放，请及时查收。感谢你的配合和支持！

○ 我能够认真且不间断地完成整个调查。
○ 我不能保证认真且不间断地完成整个调查。

条件：我不能保证认真且不间断地完成整... 跳至：提交问卷 选项

Competence perception.
To what extent do you think AI/sneaker experts can select an appropriate pair of sneakers?
To what extent do you think AI/sneaker experts can do a good job in recommending an appropriate pair of sneakers? (1 = "not at all," 7 = "very much"; Longoni *et al.*, 2020).

Source(s): Authors own work

Instruction of Study 3

旅游项目调查

您好，
我们是[illegible]大学消费行为课题组的成员，现在正在进行一项关于旅游项目选择的调查，请您根据自己的偏好选择，所有作答都是匿名的，答案没有对错之分，完成作答您将获得五元报酬。感谢您的支持！

Adoption intention.
To what extent would you like to adopt the tourist route? (1 = “not at all,” 7 = “very much”).
Complexity perception.
How complex do you think the task of developing a tourist route is?(1 = “not at all,” 7 = “very complex”).

Source(s): Authors own work

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